CONTROL OF pH IN A LABORATORY FERMENTER USING NEURO-FUZZY TECHNIQUE

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Abstract: This contribution offers a new strategy, to augment the pH process control in a laboratory scale fermenter, based on inverse neural plant model. An integration term is introduced to improve the pure neural controller performance. This element, adjusted by a fuzzy system with respect to the control error, operates in parallel with neural controller to ensure offset-free performance in case of system uncertainties or model mismatch. Four fuzzy rules were applied to generate the integrator parameters. Experimental results demonstrate the usefulness of the fuzzy integrating term and the robustness of the proposed control system.

Keywords: pH control, neural networks, inverse dynamics, fuzzy system

1. INTRODUCTION

The problem of successful identification and control of biochemical processes is continually in focus in respect of further development and improvement of performance of biochemical technologies. One of the significant process parameters to be controlled is pH.

The control of pH is a typical problem found in a variety of industries including wastewater treatment, biotechnology, chemical processing and pharmaceuticals. It is known that the pH neutralization processes are difficult to control. The possible difficulties may arise from the quality of process or reagent liquids, the type and size of the mixing reactor, the accuracy of the instrumentation, the (possibly time-variant) non-linearity of the process, and the difficulties in reliable measurement of the pH value. The non-linear character of a pH process usually means that it can be controlled by fixed parameter linear controllers, with difficulties only.

For efficient model-based control, an accurate dynamic process model is required. For non-linear processes driven through the whole operating range, linear models become impractical. Furthermore, in many industrial applications, physical constraints are imposed on process inputs. All these influent not only the problem of non-linear process modeling, but also the problem of controller output calculation, since the analytical solution to the optimization problem is no longer available. General dynamic models of the pH neutralization processes, which were involving ion balances and chemical equilibrium, have been discussed earlier by McAvoy, *et al*. (1972). They derived a mathematical model from the first principles, material balances, and chemical equilibrium. Gustafsson and Waller (1992) developed an adaptive non-linear controller for the pH neutralization process. This approach was shown to provide superior regulation performance over the conventional PID and linear adaptive controllers

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where the process characteristics had been well known. Wright and Kravaris (1991) developed strong acid equivalent based control, which is a non-adaptive control strategy.

Non-linear system identification and control have recently received considerable attention in control engineering because many industrial processes, such as chemical processes, biotechnological and food manufacturing processes, exhibit a certain type of non-linearity. All these processes are also very often affected by unknown disturbances that make the implementation of robust control systems more difficult. Adequate solutions for non-linear modelling are artificial neural networks (ANN), proven to be capable of approximating any non-linear function to a desired accuracy (Hornik, *et al.*, 1989). There are many works pointed to the neural control of pH process. Narendra and Parthasarathy (1990) developed ANN models for identification and control of desired pH in the laboratory set-up of fermenter. In (Loh, *et al.*, 1995), there is proposed a control approach to pH processes using ANN models in combination with conventional PID controller. A neural control method, based on inverse neural plant model and augmented by a robust term, is applied to a laboratory fermenter and presented in (Mészáros, *et al.*, 2002a).

Herein, the presented control technique is also based on inverse neural model, which operates in parallel with fuzzy integration term in order to ensure offset-free performance in case of model mismatch or unmeasured disturbances. Robustness of this strategy was verified by pH process control experiments in a laboratory-scale fermenter. The main goal of the resulting control system is to maintain a desired profile of pH in the fermenter by manipulating the base flow-rate. Experimental results demonstrate the usefulness of the fuzzy integrating term and the robustness of the proposed control system.

2. INVERSE pH PROCESS MODELLING

The pH is a measurement of the concentration of hydronium ions $[H_3O^+]$ in aqueous solution. Hence, the pH control is, in fact, concentration control of a mixing process and, consequently, exhibits the characteristics of mixing processes, such as mixing dead-time, residence time and dynamic gain. However, pH control also has its own unique attributes, the most distinctive of which is characterized by a neutralization or titration curve. pH is the negative logarithm of hydronium ion concentration, and this results in the 'S' shaped titration curve which defines the steady-state characteristics of a pH process (Fig. 1). Because of the logarithmic non-linearity, it is possible for the gain of a pH process to change by as much as a factor of 10 per pH unit.

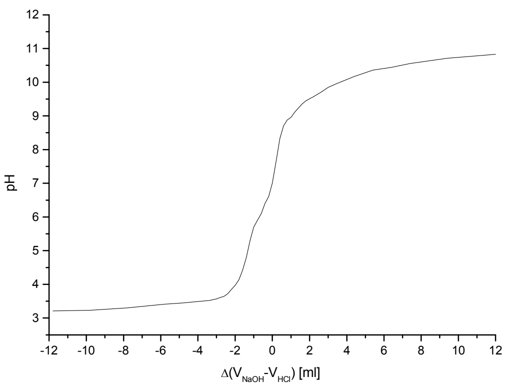

Fig. 1. Titration curve of the pH process.

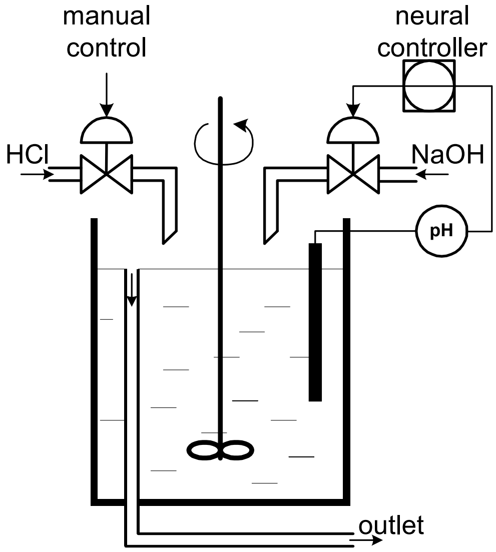

Fig. 2. The pH process scheme.

Consider the laboratory fermenter under operation, where a hydrochloride acid (HCl) of fluctuating flow-rate is continuously neutralized by sodium hydroxide (NaOH) as a manipulated variable. Neural controller is employed to compute the manipulated variable profile assuring the desired pH values. The concentration of both reagents is 0.1 mol/l. The steady-state of process occurs when the concentrations of hydronium and hydroxyl ions are equivalent. The nominal steady-state acid flow-rate (F_a^*) as well as the base flow-rate (F_b^*) equal to 2 ml/min and correspond to pH value of 7, naturally. It is assumed that the mixing is instantaneous, and the temperature, volume and the density of the mixture are constant. The simplified scheme of such a pH process is depicted in Fig. 2.

A successful control design is preceded by precise identification of the controlled process. For this purpose, an identification strategy, utilising the advantages of artificial neural network models is introduced. Application of neural networks in role of controller is mostly connected with inverse neural model (Mészáros *et al.*, 1997; Ramasamy *et al.*, 1995). In this case a neural network is trained in such a way that it represents inverse dynamics of the controlled process. Then, the proposed control system uses the inverse neural model as a direct feedback controller. A two-layer ANN model has been designed for identification of inverse pH process dynamics in the laboratory set-up of fermenter described above. The structure of ANN model used takes the form of a 3-2-1 configuration (3 neurons in input layer, 2 neurons in hidden layer and 1 neuron in output layer). The Levenberg-Marquradt training algorithm was used to train network. The network input was fed with data set containing the future values of pH ($pH(t+1)$), the difference $\Delta pH(t)$ between future and actual values of pH, as follows

$$\Delta pH(t) = pH(t+1) - pH(t) \tag{1}$$

and the past values of difference $\Delta F_b(t-1)$ between base flow-rate and nominal flow-rate, i.e.

$$\Delta F_b(t-1) = F_b(t-1) - F_b^* \tag{2}$$

At the output layer, the actual value of $\Delta F_b(t)$ was predicted (Fig. 3). The training set contained 953 samples, which were collected from the process every 10 seconds. The training error took the values below 5.10^{-2} after 300 epochs, approximately. The comparison of inverse neural model prediction and testing process data can be seen in Fig. 4.

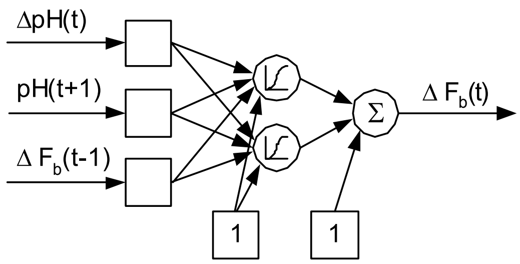

Fig. 3. Structure of inverse neural model.

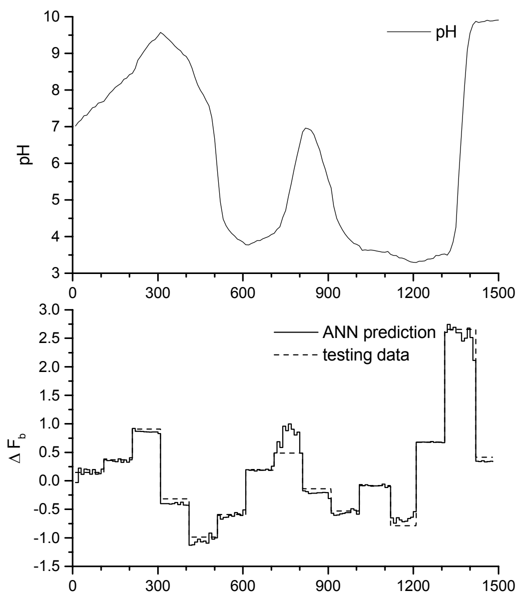

Fig. 4. Test of inverse neural model on testing set of pH process data.

3. THE NEURO-FUZZY CONTROL SYSTEM

The neural model in a role of controller has to be trained accurately to avoid model mismatch problems. However, the well trained direct neural controller gives satisfactory and offset-free results for the nominal controlled plant, only. In practice, it is not effective to train the ANN as long as to achieve the exact inverse dynamics because it may be strongly time-consuming process to get zero training error. Moreover, most of the plants in chemical or biochemical technologies exhibit time-variant non-linear characteristics and may be corrupted with unpredictable disturbances and uncertainties. As a result, the nominal performance cannot be achieved and some adaptation of the pure inverse controller is required. The online adaptation of entire network is a time-consuming process and, thus, the preferred methods for network adaptation are those, which adjust only few controller parameters. Andrášik, *et al.* (2004), have used two networks: the first one was employed as a predictive hybrid plant model of the controlled plant, and the second one was a neural, PID-like controller, which has been pre-trained off-line as an inverse black-box model of the controlled process. In order to ensure offset-free performance, the controller has been trained through three PID weights of PID neurons. A different method of the neural controller adaptation can be achieved using an additional adapter adjusting the output from neural network through bias neuron (Ramasamy, *et al.*, 1995).

The control strategy presented herein is based on principles outlined first in (Šperka and Mészáros, 2004; Mészáros, *et al.*, 2002b), where it was shown, that presence of some integration term is inevitable in control loop, but, even involving this, the control performance may turn up unsatisfactory in terms of regulation time and overshoot. It has been shown that these negative effects may result from self-characteristic of adapter (pure integrator) and incorrect timing of adaptation. In effort to improve the pure inverse controller performance, the simple integrator is replaced by a fuzzy one, which results in the structure shown in Fig. 5. The inputs of $pH(t+1)$ are replaced by reference values of pH r_{pH} and the difference, $\Delta pH(t)$, is substituted by the control error, e. The neural controller computes the difference ΔF_b from nominal base flow only. In order to obtain the value of F_b as manipulated variable, the

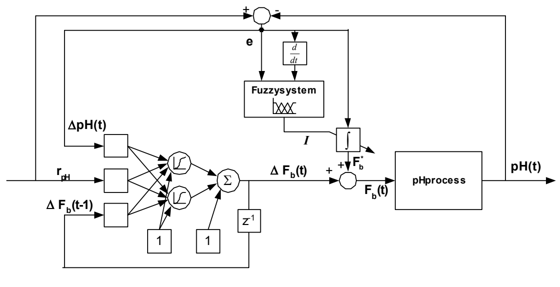

Fig. 5. The neuro-fuzzy control structure.

following equation has to be satisfied:

$$F_b = F_b^* + \Delta F_b \qquad (3)$$

The value of the nominal base flow-rate, F_b^* is the initial output value of the fuzzy integration term, which readjusts it in course of regulation with respect to the control error and its derivation. This allows the controller to adapt to changing operation conditions caused by acid flow fluctuations and, such, to compensate the new acid equivalent.

The rules and membership functions of fuzzy controller were designed in order to satisfy the following two principles:

1. Adaptation speed has to be minimal after step change of set-point value (minimal *I*-parameter)
2. As the offset appears, adaptation speed reaches maximal value (maximal *I*-parameter value)

The fuzzy system satisfying the above two principles can be defined as follows:

Input variables: ***e*** - set-point error
de - derivation of set-point error
Output variable: ***I*** - integration constant
Rule base:

1. If *e* is zero and *de* is zero, then *I* is maximal
2. If *e* is zero and *de* is non-zero, then *I* is middle
3. If *e* is non-zero a *de* is zero, then *I* is middle
4. If *e* is non-zero a *de* is non-zero, then *I* is minimal

Seven fuzzy sets are defined: two for variable *e*, two for variable *de* and three for variable *I*. In fact, defining five membership functions (Fig. 6.) is enough because fuzzy set non-zero is the complement of fuzzy set zero for both *e* and *de* variables. Gaussian MF were chosen for input variables, triangular and trapezoid MF define membership to output fuzzy set. The output surface of fuzzy controller is depicted in Fig. 7.

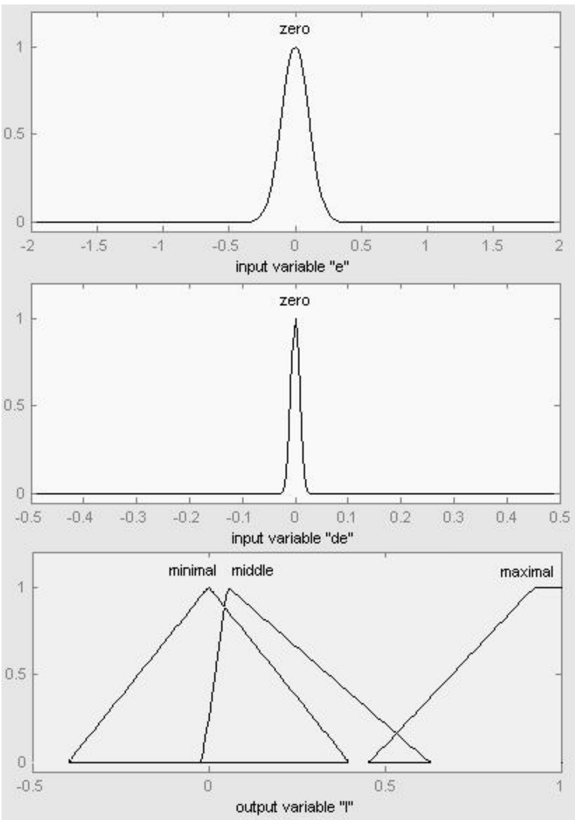

Fig. 6. Membership functions.

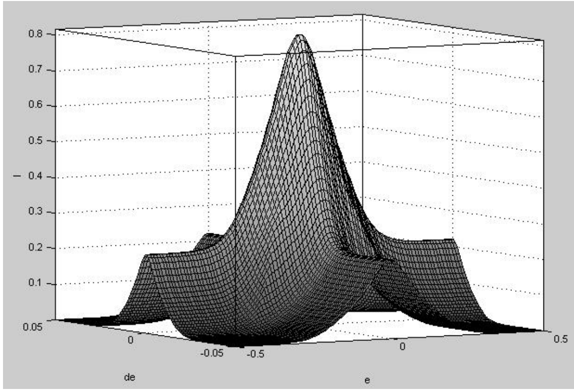

Fig. 7. Output surface of fuzzy controller.

4. EXPERIMENTAL RESULTS

Several experiments were carried out to compare performance of the following controllers: pure inverse neural controller, neuro-fuzzy controller and neural controller with simple integrator (same structure as shown in Fig. 5, where fuzzy controller is replaced by constant *I* value)

4.1 Inverse neural controller vs. neuro-fuzzy controller.

These experiments were designed to compare inverse neural controller with inverse neuro-fuzzy controller (INFC) performance while the nominal process was controlled. From Fig. 8, it can be seen, that the pH profiles and the manipulated variable profiles are comparable. The inverse neural model is accurate enough to control nominal plant and therefore minimal adaptation is required. The weakness of the pure inverse neural controller can be seen in Fig. 9 and Fig. 10, where this controller is not able to eliminate offset. The performance of INFC is satisfactory but small oscillations occur at some values of pH. This is probably caused by non-linear characteristics of the overall system as well as noisy measurement.

4.2 Disturbance rejection performance of INFC.

In this experiment, the regulatory performance was tested on pH process, where the perturbations in acid flow-rate in a range ±30% from nominal value were applied. The INFC shows good disturbance rejection performance, as can be seen in Fig. 11. The INFC adjust the nominal base flow-rate to new equivalent flow for higher acid flow-rate (area between 750s and 1050s) as well as lower acid rates (1400s – 1650s).

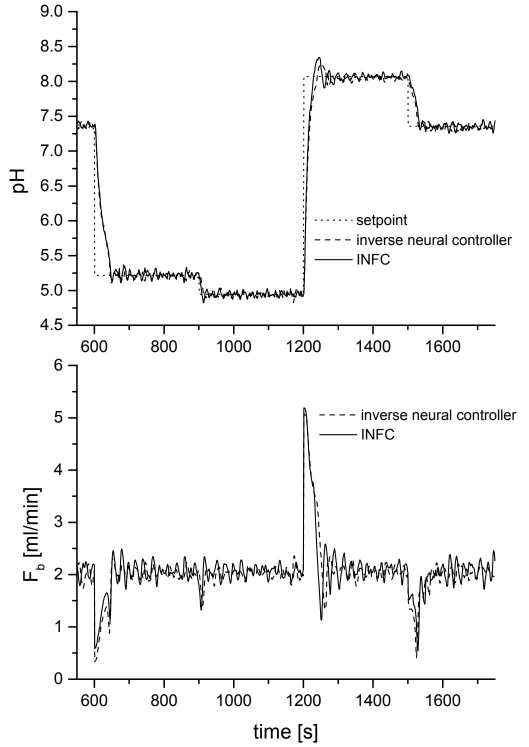

Fig. 8. Comparison of inverse controller and INFC performance while nominal plant is controlled.

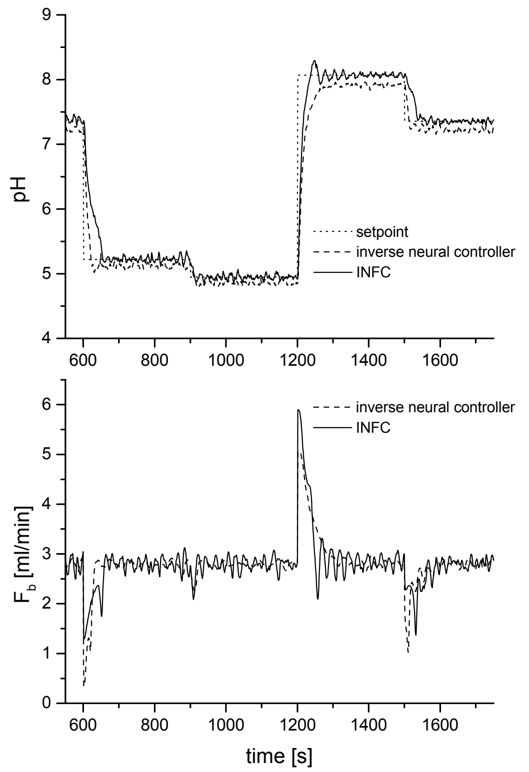

Fig. 9. Comparison of inverse controller and INFC performance – step change perturbation in acid flow-rate of +30% from nominal value

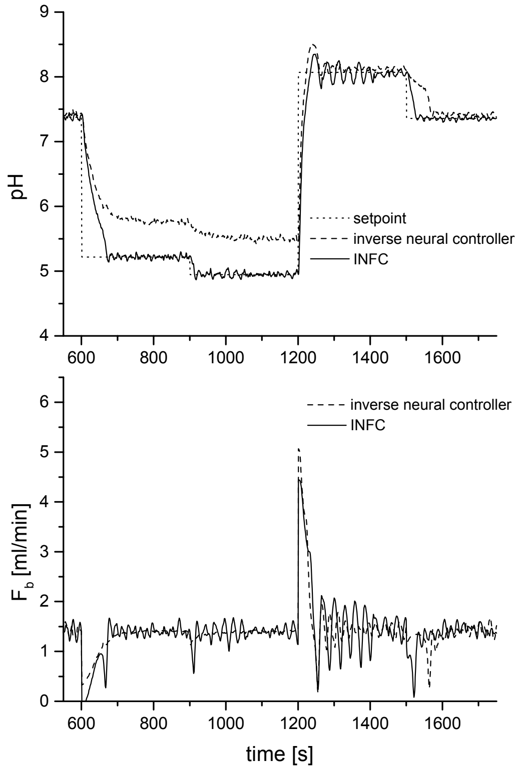

Fig. 10. Comparison of inverse controller and INFC performance – step change perturbation in acid flow-rate of -30% from nominal value.

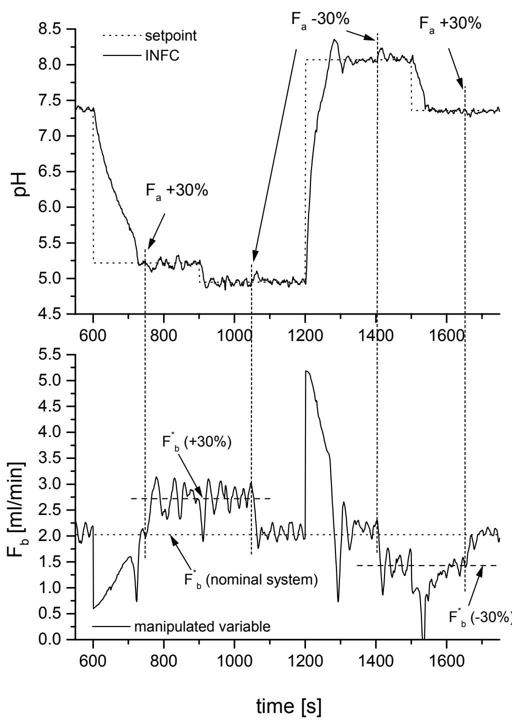

Fig. 11. Disturbance rejection performance of INFC.

4.3 Comparison of INFC with inverse neural controller involving simple integrator.

The performance of inverse neural controller working in parallel with simple integrator is

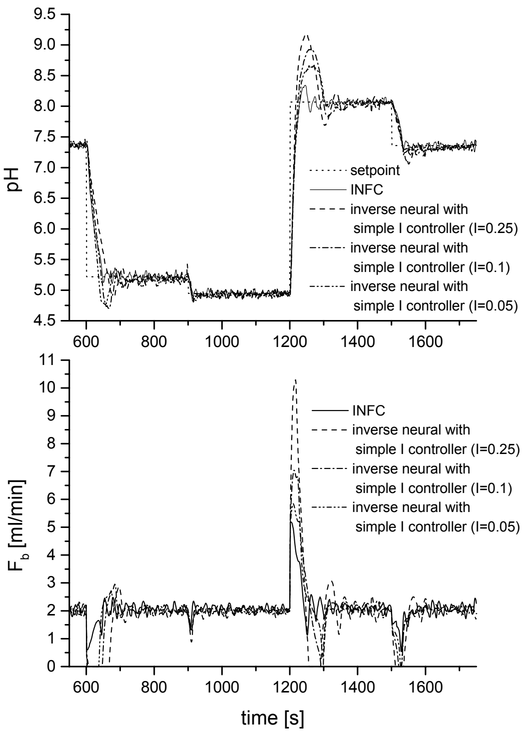

Fig. 12. Comparison of inverse controller with simple integrator and INFC performance – nominal plant.

characterized by higher values of overshoot and longer regulation times, as shown in Fig. 12. The overshoot occurs even if the nominal plant is controlled. Fuzzy controller of INFC ensures correct timing of adaptation, which leads to overshoot elimination.

5. CONCLUSION

A new strategy of non-linear plant control in presence of system uncertainties and possible model mismatch has been introduced. The proposed control system is based on neural network inverse plant model and utilises fuzzy adjustment of the augmented integration controller term. Application to a laboratory scale pH process has demonstrated the advantages of the innovative technique. Comparison with more conventional neural approaches has confirmed the superiority of the combined neuro-fuzzy approach in both, regulatory and tracking aspects.

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